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Multi-criteria human resources planning optimisation using genetic algorithms enhanced with MCDA

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Abstract

The main objective of this paper is to present an example of the IT system implementation with advanced mathematical optimisation for job scheduling. The proposed genetic procedure leads to the Pareto front, and the application of the multiple criteria decision aiding (MCDA) approach allows extraction of the final solution. Definition of the key performance indicator (KPI), reflecting relevant features of the solutions, and the efficiency of the genetic procedure provide the Pareto front comprising the representative set of feasible solutions. The application of chosen MCDA, namely elimination et choix traduisant la réalité (ELECTRE) method, allows for the elicitation of the decision maker (DM) preferences and subsequently leads to the final solution. This solution fulfils all of the DM expectations and constitutes the best trade-off between considered KPIs. The proposed method is an efficient combination of genetic optimisation and the MCDA method.

Keywords: *mathematical optimisation, multi-criteria optimisation, scheduling, job-shop problem, MCDA*

1. Introduction

Employee scheduling has been a common problem in the literature since the 1950s [51]. This can be a crucial process due to at least two reasons: high labour costs, which can be reduced by proper scheduling, and a labour shortage in which loss of profit can be minimised by optimising human resources planning [62].

Beaker [3] proposed three classes of personnel scheduling problems: shift scheduling, day-off scheduling, and rotating scheduling. Shift scheduling is the simplest one where the daily planning horizon is considered with either overlapping or non-overlapping shifts. In day-off scheduling employee's workweek is of a different length than the operation week. The most common example is the five days workweek

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and two free days with an operational week, altogether lasting for seven days. Rotating scheduling is a combination of both previous models. A company works seven days a week and each day consists of more than one shift. Employees do not have a fixed schedule, thus workweek can be of different lengths but the required daily and weekly breaks have to be satisfied.

Different types of methods can be used to solve a personnel scheduling problem. Yakoob et al. [1] proposed a classification with ten classes: (1) manual solution, (2) integer programming, (3) implicit modelling, (4) decomposition, (5) goal programming, (6) working set generation, (7) linear programming-based solution, (8) construction/improvement, (9) metaheuristics, and (10) other methods.

Personnel scheduling is computationally complex, in a general case, NP-complex problem. Due to its non-polynomial complexity, only small instances can be treated with systematic approaches like linear programming or mixed-integer programming [9]. For larger problems, which are more common in real-world applications, heuristics that introduce a trade-off between the time of computations and the quality of results have to be used [53].

Real-world personnel scheduling is a multi-objective problem where criteria such as length of the schedule, utilisation of resources, the satisfaction of people's preferences, and compliance with regulations have to be considered [59]. To address the multi-criteria nature of this problem optimisation algorithms designed for a multi-objective goal function were used [45], including the multi-objective genetic algorithms [14]. Proposed here non-dominated sorting genetic algorithm II (NSGAII) methodology is broadly applied for scheduling problems [4, 38, 44] as well as in many other areas [2, 17, 36, 57, 64, 67]. The method is designed for efficient handling of the multi-objective optimisation problems providing high-quality, uniformly distributed approximated Pareto frontier.

Within the current study, we propose a novel hybrid approach which combines the NSGAII method with the ELECTRE approach. This combined methodology provides a tool which is capable of determining a Pareto-optimal solution fulfilling the current quality expectations. For an in-depth review of the applications of the NSGAII framework in the area of scheduling see [53]. The problem addressed in the presented research is a standard and frequently encountered business scheduling problem. Within this business case, the task of scheduling algorithms is to find the best possible match between transportation tasks and workers. In operations research, this type of problem is called the job-shop problem. From a formal point of view, it means that there is a finite number of jobs, a set denoted by J, and a finite number of resources, a set denoted by M. The mathematical goal is to find the best solution being the best match between the task and resources. It is an NP-complex problem, its complexity is non-polynomial and grows very fast with the number of tasks and the number of resources. Thus, it is necessary to design and use efficient heuristics to find approximate, possibly good solutions.

The remaining of this paper is organised as follows: Section 2 introduces the general business context of the problem, Section 3 provides the discussion about the business rules and constraints as well as the considered here KPIs are defined there. In Section 4 the NSGAII and ELECTRE are thoroughly discussed with an emphasis on the synergy between these two. In Section 5, the attention of the reader is focused on the numerical experiments and the results and finally, in Section 6, the conclusions are formulated.

2. Business context of labour planning

Resource planning remains one of the fundamental problems in economic science. Planning is a specific element of corporate decision-making that relates to the future of an organisation. It is one of the four key elements of the management process. Generally, it is continuous and is also a reflection of the changes taking place in the organisation [61]. Planning is a strategic function and produces results in the long term [65]. Planning allows one to properly approach the implemented activities and to determine its priorities or to maximally use the available competencies [43]. Resource planning is often equated with work planning in manufacturing (production plant). Therefore, much of the literature on job-shop refers to the optimisation of production planning. Some authors, especially those interested in computer scheduling, refer also to these machines as processors because each activity means an operation for a machine [23]. In turn, analysing the literature on multi-criteria scheduling, it can be seen that de facto individual job execution scenarios imply the execution of different job parameters – and the value of each parameter is related to the job and the specific scenario. This makes scenario analysis a complex problem [28]. The choice of mathematical methods also remains an interesting problem, addressed by researchers both directly in relation to urban transport and more broadly, for example in the context of resource planning in supply chains [27]. In essence, the problems of the two mentioned areas are similar. Resource planning and task scheduling also remain an interesting issue wherever these processes are carried out in a decentralised manner – there too, the potential for supporting these processes with appropriate software is seen today [26]. More and more often various simulation and machine learning techniques are also being used to support planning in manufacturing processes and beyond [58]. At the same time, planning on defined metrics allows for being more tailored to the specific business [66].

3. The economical efficiency of labour planning

The discussed case of scheduling tasks is a real business problem for a public transport operator providing public transport services with the use of buses and trams. Miejskie Przedsiębiorstwo Komunikacyjne w Poznaniu (Municipal Public Transport Company) operates a fleet of approximately 600 vehicles. Clearly, it faces the necessity of planning the work of approx. 800 bus drivers and 600 tram drivers. Due to the continuous development of the department responsible for task scheduling and increasingly complex scheduling issues, a strategic decision was made to implement a new IT solution for the job scheduling of these 1400 employees. The mathematical algorithms are part of an IT system implemented for this purpose. The implemented IT system was related to the creation and development of comprehensive tools which allow maximisation of the efficiency of working time management: implementation of a system for job planning, supervision of job planning implementation and clearance of workers' jobs.

In the context of this issue, the basic data set are transport tasks (shifts). They define specific tasks to be realised by specific vehicles – separated vehicles on each bus line or tram line. Each shift characterise the parameters: start time, end time, duration, driving time or rolling stock type, and others.

On the other hand, within the second set of data, there is a group of all available employees. Each of them has certain, individual characteristics like type of contract, nominal working hours, holiday volume or specific days that can be planned for work or days off.

The idea of scheduling is to pair shifts and workers. This has to be a 1:1 relationship – for obvious reasons a vacant vehicle would not leave the depot, with few exceptions the presence of two drivers in one vehicle would not make sense either. In practice, transport tasks also have features that act as business constraints – for example in terms of the planned type of rolling stock. Employees also have defined qualifications. So if, for example, a specific job defines a type of rolling stock, it is necessary at the planning stage to take into account the qualification for that type of rolling stock that the specific employee is equipped with. This clearly increases the complexity of the planning problem, especially in tram operations where the number of rolling stock types can reach a dozen.

In the discussed enterprise, much attention is paid to the issue of work planning, among others due to the difficult labour market. The continuous shortage of bus and tram drivers makes planning work one of the most difficult tasks in operational management. This is an effect of a phenomenon called employee market, i.e., permanent shortage of employees supply. This phenomenon, in relation to professional drivers, is observed practically in all larger Polish cities.

One of the main challenges at the implementation stage of the optimisation algorithms was to take into account all the requirements: different criteria and constraints. The resource planning business process itself has four stages. The layout of the stages is shown in Figure 1. It should be noted that this process has the nature of feedback – the stage of implementation of the carriage is also a source of data for subsequent stages of the planning process.

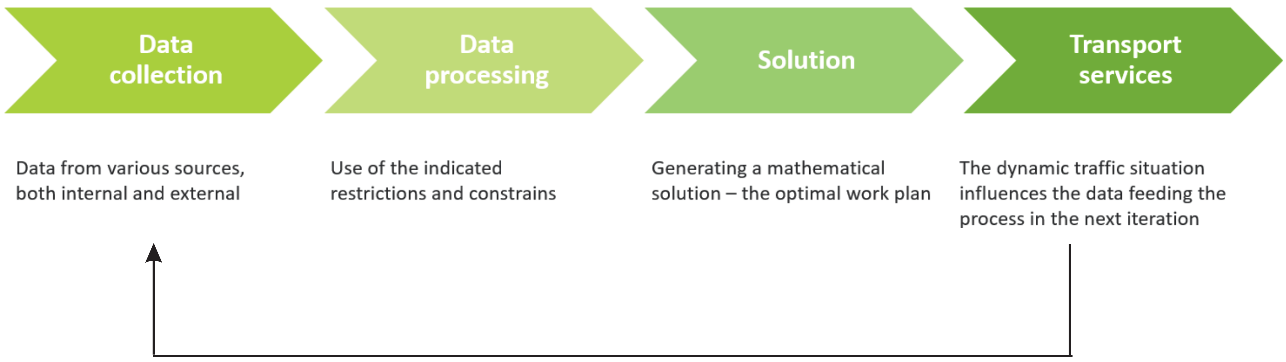

Figure 1. Resource planning business process

From the organisation's point of view, all these stages focus on the successive collection and entering information into the system about:

- previously known absences of employees (e.g., long-term absences),
- restrictions on employees (e.g., their availability schedules),
- assignments to employee groups (in case of group planning or over a planning period longer than one month),
- availability on specific dates (e.g., for employment/ dismissal).

This data is entered manually using dedicated views, and in some cases imported from external systems (e.g., ERP systems).

Three levels of data are used in the planning process (as well as in the entire planning information system): the monthly plan, the updated monthly plan (as a daily plan, called "shifts list") and the execution (the a posteriori information about the executed schedule). Planning with the optimisation engine is done at the first level, but taking into account the plan update and execution data as far as it is possible and data are available.

3.1. Business rules and constraints

The essential task of mathematical algorithms is to create a monthly work schedule. This schedule must take into account basic business-like constraints. Planning constraints can be divided into several basic groups and according to different criteria, namely:

- mandatory and optional restrictions (preferences, business rules),
- external and internal constraints,
- restrictions concerning the employee, working hours and days or holidays.

The primary pieces of legislation outlining work planning requirements are:

- labour Code,
- drivers' Hours of Work Act,
- internal regulations (work regulations, company collective agreement and others),
- provisions specifying the requirements for medical, psychological and other health and vocational qualifications.

In the case of bus drivers and tram drivers, the so-called equivalent working time is usually used as the basic working time system. According to art. 129. §1 of the Labour Code Act, "working time cannot exceed 8 hours per day and an average of 40 hours in an average five-day working week". This provision is complemented by article 135. §1 of the Act: "if it is justified by the type of work or its organisation, the system of equivalent working time may be used, in which it is permissible to extend the daily working time, but not more than to 12 hours, in the settlement period not exceeding 1 month. The extended daily working time is balanced by a shorter daily working time on certain days or by days off". These provisions allow for more flexible scheduling wherever it is necessary to fill jobs in a two- or three-shift system or on holidays.

In practice, this means that bus and tram drivers, in accordance with the regulations of the Labour Code, can perform shifts up to 12 hours on selected days of the month (not necessarily only from Monday to Friday, but also on Saturdays, Sundays and holidays). The limit for the number of working days in a month is therefore 8 hours multiplied by the number of working days, which usually means a range of 152–184 hours for a full-time employee. Of course, these are just a few of the many rules, resulting not only from the Labour Code but also from other legal regulations. Additional restrictions (for example up to 10 hours of working time) result from the Act about drivers working time. In order to stay according to the law, the planning algorithms have taken into account the limitations of both Acts.

Selected constraint items from the implemented algorithms are presented in Table 1. Due to the complexity of the planning problem, authors have limited themselves to presenting the key constraints for planning processes. However, it should be noted that there are several dozen of these constraints in the system and all of them are taken into account by the planning algorithms. This is the reason why the task-employee matching process is the most time-demanding step of the algorithm.

Table 1 contains both formal and legal restrictions, resulting from existing legal regulations and those developed as good practices over the years of the company's operation. Both of these groups are interesting. In practice, the second optional group may also be considered obligated, when they have a key and clear influence on the quality of planning or subsequent execution of transport tasks.

Table 1. Selected limitations of work planning

Limitation	Type	Source
Daily rest (11h), weekly rest (24/35h)	obligatory	legislation; act about drivers working time
Maximum working time limits (10 hours per day, 60 hours per week)	obligatory	legislation; act about drivers working time
Number of days off not less than the calendar	obligatory	legislation; labour code
Validity of periodic and psychological tests	obligatory	law
Validity of authorisations for a specific type of rolling stock	obligatory	internal regulations
Staff availability preferences (hours from/to, selected days)	optional	information from employees

To discuss an example, it will be a value to look at the parameter concerning the maximum number of working activities day by day. Although the law allows for planning cycles of up to six days, due to the nature of the work performed (shift work, high level of stress, changing climate conditions) it is desirable to eliminate the sixth day of work. This allows the reduction of the engagement of employees, and the distribution of the workload more evenly over the month. On the other hand, scheduling of single days of work (a day off, a day of work and again a day off), although also not prohibited by law, is eliminated in order to increase the comfort of employees. It also allows for a better grouping of days off, and, statistically, employees more often receive a sequence of two days off (which corresponds to a typical weekend). This constraint is an example of both obligatory constraint (1–6 days of continuous work) and optional constraint (2–5 days of work on consecutive days). To reconcile these two perspectives, the types of constraints take the form of configurable parameters in the system in most cases.

Some restrictions are relative in nature – they depend on other restrictions and the specific tasks performed by the employee. For example, there is a concept of a working day which limits the working day for an employee. For employees which work on the 1st and 2nd shifts, a day is contained in the time period between 3.00 AM and 3.00 AM, and for those who perform also night duties – between 8.00 AM and 8.00 AM. Since the second group is on duty only during the 2nd and 3rd shifts (without the 1st, which means morning shifts), the next task of optimisation algorithms is to appropriately balance task scheduling between workers on the 3rd shift. Planning night tasks (due to the rigid group of employees handling them) has a higher priority. The remaining tasks must be balanced – completing the nominal hours of night workers and between the remaining workers.

Proper distribution of free days (days off) remains a separate, important planning topic. An employee is entitled to have the days off for Sunday (Wn – free for Sunday), for holidays (Ws – free for holiday) and for ensuring a five-day working week (Wd – additional days off for Saturday). Each type of day off may have defined criteria of occurrence, which is an additional limitation for scheduling algorithms. The scheduling algorithm allocates the appropriate amount of time off according to the defined rules. The most important of these rules are:

- every fourth Sunday off (free Sunday may occur more often),
- days off not less than the nominal number of days off (Saturdays, Sundays, holidays) in the given planning period,

- day off for Sunday must be scheduled within six days before or six days after this Sunday,
- holiday and Wd's day off may be scheduled on any day within the planning period (provided it is not a Sunday or a holiday),
- if Sunday and the public holiday fall on a Sunday or public holiday, it may not be taken on another day.

The scheduling algorithm also takes into account all additional activities that are delivered as input data – absences (illnesses, holidays according to the dictionary of types) or training (including defined types of training in specific hours, e.g., OSH training). For each type of activity, there are defined assumptions for later settlement – whether it is a paid or unpaid day, whether it is included in the employee's nominal value or generates overtime etc.

The input data about employees is collected in the "Employee file". This is all the information that refers to individual employees, and from the perspective of scheduling algorithms, the most important is the information that may limit an employee's availability, or otherwise specify limitations or preferences for scheduling.

3.2. Key performance indicators (KPIs)

Algorithms responsible for assigning workers to tasks follow certain optimisation directions based on defined KPIs. Each indicator has a numerical parameter associated with it, called the goal function priority, which reflects to what extent the optimiser should take into account the given goal function. This allows the DM to influence the optimisation process.

A total of over a dozen key indicators were defined to assess the quality of the plan and to match the plan to DM preferences. Key indicators are these, which relate to the main directions of multi-criteria optimisation. These indicators are:

- General task planning – determines the percentage of shifts to which an employee is assigned in relation to all shifts from a given planning period (that means actually: task planning index) in the considered planning horizon. The indicator is applied to morning, afternoon and night shifts (1st, 2nd and 3rd shift).
- Equality of deficiencies – the purpose of the KPI is to determine the uniform distribution of unassigned tasks over a given planning period.
- Home depot indicator – specifies the number of shifts assigned within the home depot to the total number of shifts (working days). This indicator characterises the plan, the optimiser should strive to make this value as high as possible. Additionally, the distribution of assignments from outside the home depot should be equal among the employees.
- Equality of 2nd shift scheduling – assigning second shifts of afternoon services to employees assigned to the night schedule. This is the standard deviation of the number of hours resulting from afternoon shifts assigned to night workers.
- Number of switches between the 1st and 2nd shift – if such transitions are allowed, then one of the criteria for schedule quality is a number of them.

Such indicators are complemented by KPIs of qualitative nature. For instance, a special mechanism was implemented to ensure the implementation of the "diversity of reserves" factor. The diversity of the length of the generated reserves should be as high as possible, which allows for matching the reserves with the shortfalls in the transport tasks in a given month. The length of the generated reserves is adjusted to the current transport tasks.

Among the KPIs there are also informative indicators which form the basis for plan evaluation for the planner responsible for creating work schedules dedicated to a group of employees (from a given depot or traction). These include indicators related to planning execution (measured at the stage of subsequent plan implementation), service list variability (number of reserves per employee planned and executed), the average length of service (average duration of service divided into shifts and types of days per depot) or the length of non-issued shifts (calculated according to defined time intervals).

3.3. Financial aspects

Scheduling optimisation's main aim, among other issues, is maximising the efficient use of labour. In public transport, shifts for drivers and co-drivers have different lengths, so it is usually impossible to plan the entire monthly hourly quota down to the minute. As a result, some activities are not desirable from the employer's point of view, but necessary to fill the employee's calendar nomination. They are called "plus reserves" (so-called, because they are an addition to the employee's shifts), and in fact, they are lost working time. The employee is formally at work, but usually, it is a short time, which does not allow any use of the employee's availability. Minimising plus reserves is an important planning goal.

A second important objective of planning is to minimise the level of overtime. Proper scheduling – as balanced as possible and with maximum utilisation of the available working time – makes it possible to reduce the amount of overtime – which, in turn, represents financial value for the company. The better the scheduling, the less overtime is worked. Of course, to a certain level, due to the insufficient number of employees, overtime naturally occurs anyway. In practice, the algorithm responsible for scheduling is therefore designed to create a plan that minimises additional costs (e.g., overtime). Obviously, in the case of a shortage of workers, it is impossible to ensure full staffing for the implemented tasks – the task of the algorithms is then to maximise this staffing, as well as to ensure the possibility of employing workers in additional time.

4. Methods

A single-objective optimisation (SOO) is a set of procedures routinely applied in different areas of industry and science. As the name says, the SOO methods focus on problems where only one goal function is considered, and the decision vector is a subject of optimisation according to this goal function. A variety of algorithms solving that task were proposed, e.g., simulated annealing [41], local search, Tabu search [29], or genetic algorithm [30]. On the other hand, the multi-objective optimisation (MOO) problems, are designed to tackle qualitatively different problems, where multiple objective functions exist and must be respected simultaneously. Here, instead of finding the optimum with respect to a single goal, one needs to cope with multiple objectives, often conflicting with each other. The interactions between goals result in multiple solutions for a particular problem, usually called trade-offs, non-dominated, non-inferior or Pareto-optimal solutions. The multi-objective optimisation problems are successfully addressed by many approaches [40], one of them is the family of multi-objective genetic algorithm (MOGA), which was proposed as a generalization of the single-objective genetic algorithm [48]. There are multiple variants of MOGA methods such as strength Pareto evolutionary algorithm (SPEA and SPEAII) [68], Pareto archived evolution strategy (PAES) [42], Pareto envelope-based selection algorithm (PESA, PESAII) [13], Niched Pareto genetic algorithm [35] and many others [21]. The presented research focuses on the application of the NSGAII [16] in a scheduling problem.

4.1. The NSGAII method

The NSGAII method, similar to the majority of the genetic algorithms (GA) approaches, has the usual structure involving population creation, selection and genetic operations. In particular, the key elements of the NSGAII methodology can be sketched in the following way:

1. Create an initial population.
2. Carry out the non-domination sort.
3. Calculate the crowding distance.
4. Select a new population using crowded tournament selection, where solutions are compared based on front ranking and in case of a tie by a crowding distance.
5. Apply genetic operators, i.e., create offspring.
6. If optimisation is not finished, return to Step 2.

Due to the fact that the crowding distance is taken into account explicitly, the NSGAII method tends to return an evenly distributed Pareto front. In principle, this is a desirable feature, because it assures that the solution space is spanned over a relatively large range of objective values, thus considered population covers diverse cases. This leads to a high-quality, representative, Pareto front, which ultimately delivers the final solution of desired properties, i.e., where the trade-offs between goals are at the expected level.

At the general level of consideration, the main optimisation task is, for a defined set of workers (M) and a set of tasks (J), to create a schedule by assigning a single worker m_i to a particular task j_i. Due to obvious reasons, if the availability of workers is not sufficient, some tasks remain unassigned. This problem was proven to be NP-hard [24], thus to provide a solution in a feasible time, a heuristic approach has to be used. In the presented approach the NSGAII procedure was chosen. Each chromosome, i.e., the member of the population, is represented as a presorted vector of workers (M). Such a vector processed within a deterministic algorithm leads unequivocally to an assignment of employees to tasks. The whole procedure is presented in Algorithm 1. At this level of generality, this procedure seems to be very simple. In practice, however, the crucial point is the procedure responsible for the worker-task assignment. It is a complex set of operations producing feasible solutions. Checking if m matches j, i.e., the verification of all the business constraints, requires a thorough check of all the conditions defined in Section 3.1. All the constraints defined either by Polish law or being an internal rule of the company must be explicitly verified here.

These steps are executed to transform a chromosome into a feasible solution within the NSGAII algorithm. The solution space exploration is reduced here to the exploration of potential workers' presorted vectors. This presorted vector of workers should be understood as the optimisation decision vector, fully determining the resulting schedule. The decision vectors of this form, being the chromosomes in the GA language, are the subject of all genetic operations like selection, cross-over or mutation. The resulting population is then the subject of the quality estimation by means of the KPIs defined earlier (see

Section 3.2). The assignment of the tasks to the workers can be considered as the mathematical transformation of the decision vector into the space of the KPIs. The chosen MOO method, i.e., the NSGAII approach, takes care of non-domination. This means that the genetic population approximates the Pareto frontier and each next generation of the genetic procedure improves the Pareto frontier towards the exact solution. In the end, the algorithms return the final, the best, Pareto frontier of the solutions. The final step, discussed in the next Section, is to extract a single solution which reflects the best current preferences.

```
Input: Array of workers M = [m_1, ..., m_n], Array of tasks J = [j_1, ..., j_m]
Create vector M
for j ∈ J do
    for m ∈ M do
        if m matches j then
            Assign m to j
            proceed to the next j
        end
    end
end
```

Algorithm 1. Procedure of matching tasks with workers

4.2. The application of the MCDA to the extraction of final solution

In contrast to SOO, which returns a single best solution, MOO provides a set of non-dominated solutions called a Pareto frontier. Without any additional preference information from a DM, these solutions are incomparable and represent a trade-off between metrics. The MCDA algorithms are designed in such a way that they support the DM with preference elicitation and ultimately lead to the extraction of a single solution with expected properties [11]. Within these approaches, firstly, preference information reflecting the value system of the DM is collected. Then it is applied to the dataset to provide recommendations. Some of the most popular MCDA algorithms are analytic hierarchy process (AHP) [56], dominance-based rough set approach (DRSA) [34], and family of ELECTRE methods [55]. Such algorithms are widely applied in use cases from different areas including energy [12, 25], finance [49, 60], military [15, 19, 37] or urban development [50, 52]. In particular AHP method has been applied to many real-world problems [32, 54]. However, due to DM's preferences, this method is not suitable for this use case. The preferences of the DM were as follows.

- Poor performance on one criterion cannot be fully compensated by good performance on others.
- Algorithm should directly use per-criterion pairwise comparison thresholds, in particular indifference and veto thresholds.
- Criteria expressed on different quantitative scales must be accepted

There is a variety of the MCDA approaches available, here in order to select an appropriate one we have applied the methods selection system [10]. Among them the ELECTRE [22, 55] method seems to be the most suitable for this problem while being also widely applied to real-world problems [20, 31]. The methods selection system suggested a number of methods satisfying the DM's preferences as well as meeting the problem description, e.g., PROMETHEE [7], TACTIC [63], RUBIS [6], and ELECTRE

[22, 55]. The latter was found to be preferred by the DM due to multiple real-world applications [5, 31, 46] and a variety of extensions of that approach [33, 39].

4.2.1. The ELECTRE method

The family of ELECTRE methods are based on an outranking relation S, which can be interpreted as equal or better. If one alternative outranks the other, it means that it is at least as good, based on the DM's value system, and there are no significant reasons to refute this relation.

In what follows the following notation was used:

- $A = \{a_1, a_2, \ldots, a_n\}$ – a set of decision alternatives (schedules coming from NSGAII).
- $G = \{g_1, g_2 \ldots, g_m\}$ – a family of evaluation criteria.
- $g_j(a_i)$ – the performance of alternative a_i with respect to criterion g_j. For clarity of the presentation in what follows we assume that all criteria are of gain type meaning the higher value the better.
- q_j, p_j, v_j – values of indifference, preference, and veto thresholds on criterion g_j.
- w_j – weight of criterion g_j.

4.2.2. Preference information

The DM provides two types of preference information: weights associated with each criterion and threshold values. Weights w_j represent the strength of a given criterion and should be rather associated with the number of votes than a numeric weight itself. In ELECTRE methods three thresholds are used: indifference q_j, preference p_j, and veto v_j. The first two are called intracriteria, and the last one is intercriteria. The intracriteria thresholds impact only evaluation on that criterion, while intercriteria affect general evaluation. The indifference threshold indicates a maximal difference on a given criterion that is negligible. It can help reduce noise impact when dealing with imperfect knowledge [18]. The preference threshold is a minimal difference denoting strict preference, whereas the veto threshold represents minimal difference which is so significant that it invalidates preference relation.

4.2.3. The model

In this section, we present a variant of ELECTRE that was used for the selection problem. The method constructs a matrix with the credibility of outranking relations for each pair of alternatives. That matrix is later exploited with a net flow score (NFS) procedure to calculate a score for each alternative. Finally, an alternative with the highest score is recommended.

To calculate the credibility of outranking relation, for a given ordered pair of alternatives (a, b), the following procedure is applied:

1. For each criterion g_j, calculate the marginal concordance function $c_j(a, b)$ presenting the strength of an outranking b on g_j. Value of $c_j(a, b)$ depending on $g_j(a)$ and $g_j(b)$ is presented in Figure 2 and mathematically can be expressed as:

$$c_j(a, b) = \begin{cases} 1 & g_j(a) - g_j(b) \geq -q_j \\ 0 & g_j(a) - g_j(b) < -p_j \\ \dfrac{g_j(a) - g_j(b) + p_j}{p_j - q_j} & \text{otherwise} \end{cases} \tag{1}$$

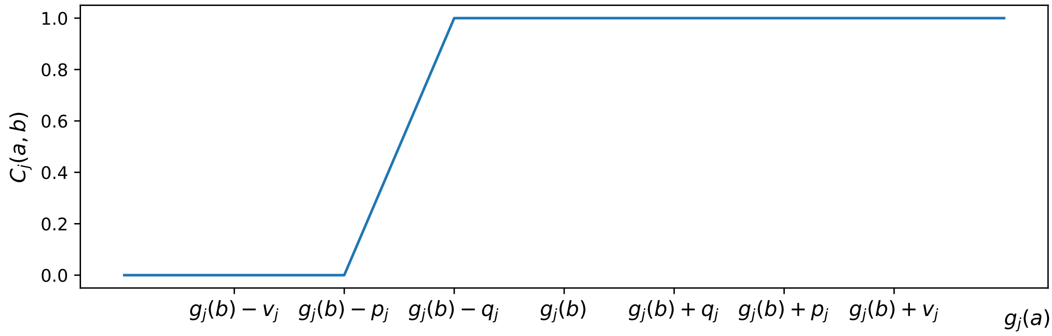

Figure 2. Dependence of the marginal concordance function on the difference between two alternatives on one criterion

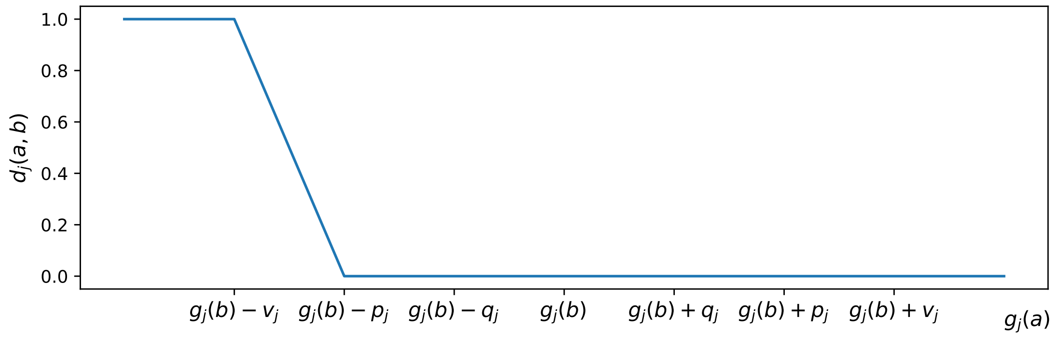

Figure 3. Dependence of marginal discordance function on the difference between two alternatives on one criterion

2. Calculate the comprehensive concordance index $C(a, b)$ which denotes the strength of an outranking b on all criteria

$$C(a, b) = \frac{\sum_{j=1}^{m} w_j c_j(a, b)}{\sum_{j=1}^{m} w_j} \tag{2}$$

3. For each criterion g_j, calculate the marginal discordance function $d_j(a, b)$ presenting the strength of negation of an outranking b on g_j. Value of $d_j(a, b)$ depending on $g_j(a)$ and $g_j(b)$ is presented in Figure 3 and mathematically can be expressed as:

$$d_j(a, b) = \begin{cases} 1 & g_j(b) - g_j(a) \geq v_j \\ 0 & g_j(b) - g_j(a) < p_j \\ \dfrac{g_j(b) - g_j(a) - p_j}{v_j - p_j} & \text{otherwise} \end{cases} \tag{3}$$

4. Calculate the credibility of an outranking relation defines as follows [47]:

$$\sigma(a, b) = C(a, b) \left(1 - \left[\max_{0<j\leq m} d_j(a, b)\right]\right) \tag{4}$$

The procedure is applied for each pair of alternatives resulting in matrix M, where $M[i, j] = \sigma(a_i, a_j)$. This matrix is then exploited using the NFS [8] procedure to calculate a score (s_i) for each alternative, which is defined as follows:

$$s_i = \varphi_i^+ - \varphi_i^- = \sum_{j=0}^{n} M\,[i, j] - \sum_{j=0}^{n} M\,[j, i] \tag{5}$$

Finally, the alternatives are ranked according to the score s_i, and the one with the highest score is returned as the final recommendation. Such an approach is more robust to the imperfect perspective of the DM. This is in opposition to approaches like ELECTRE 1s, where a subset of solutions can be selected [31], and still, the DM is obliged to make the final choice when only one alternative must be selected.

5. The results of optimisation

This section presents a discussion of the results obtained within a particular application of the optimisation approach to real data. The set of tasks contained 9003 items, and the optimisation problem was to assign them to 573 workers/employees. In the first phase, the NSGAII method was applied to obtain the Pareto front of the solutions. As already mentioned, without the additional preference information from the DM, it is impossible to point out the final solution. Therefore, within the second phase, the preference information is incorporated and utilised within the MCDA method.

The exemplary set of solutions is presented in Figure 4. The blue dots represent the feasible solutions; the orange dots reflect 14 particular solutions that form the Pareto front. The performance of these solutions is shown in Table 2.

Table 2. Pareto front of generated solutions[1]

Name	KPI1↑	KPI2↑	KPI3↑	KPI4↓	KPI5↑	KPI6↓	KPI7↓	KPI8↓
a_1	0.8683	0.8726	0.8000	74.7052	0.6296	5.5364	24.8440	0
a_2	0.8690	0.8724	0.8000	74.6285	0.6298	5.5369	24.8440	0
a_3	0.8692	0.8702	0.8000	81.8977	0.6286	5.5729	25.9767	0
a_4	0.8697	0.8699	0.7905	77.7294	0.6234	5.4849	27.8632	1
a_5	0.8713	0.8695	0.7905	67.6030	0.6218	5.4981	26.6789	0
a_6	0.8724	0.8690	0.7905	68.5985	0.6190	5.4990	28.1957	1
a_7	0.8729	0.8677	0.7905	71.5745	0.6273	5.4997	25.4752	1
a_8	0.8756	0.8672	0.7905	79.5618	0.6234	5.5155	27.8992	1
a_9	0.8770	0.8666	0.7905	63.8953	0.6281	5.5250	25.2300	1
a_{10}	0.8790	0.8652	0.7905	66.1173	0.6288	5.5110	25.6365	0
a_{11}	0.8792	0.8598	0.7905	70.3695	0.6271	5.4850	25.4279	1
a_{12}	0.8797	0.8594	0.8000	68.6371	0.6293	5.5134	25.5040	0
a_{13}	0.8822	0.8587	0.7905	68.4240	0.6222	5.4758	25.1981	0
a_{14}	0.8824	0.8542	0.7810	80.6420	0.6292	5.5265	25.4271	1

[1] Gain-type criteria are denoted by ↑, while cost-type criteria are denoted by ↓.

To illustrate the calculation phase, each step of the calculation of the credibility of the outranking relation between solutions a_{13} and a_7 is discussed in detail. The preference information used for this study is presented in Table 3. The alternative a_{13} is equal to or better than a_7 on KPIs 1, 3, 4, 6, 7, 8, thus the marginal concordance functions in these criteria are equal to one $c_j(a_{13}, a_7) = 1, j \in \{1, 3, 4, 6, 7, 8\}$.

Table 3. Indifference, preference, and veto thresholds along with the weights used for this study

Type	KPI1↑	KPI2↑	KPI3↑	KPI4↓	KPI5↑	KPI6↓	KPI7↓	KPI8↓
Indifference	0.005	0.005	0.01	1	0.002	0.01	0.5	2
Preference	0.02	0.02	0.02	3	0.005	0.03	1	3
Veto	0.05	0.05	0.05	10	0.02	0.1	5	10
Weights	5	5	3	2	2	3	2	1

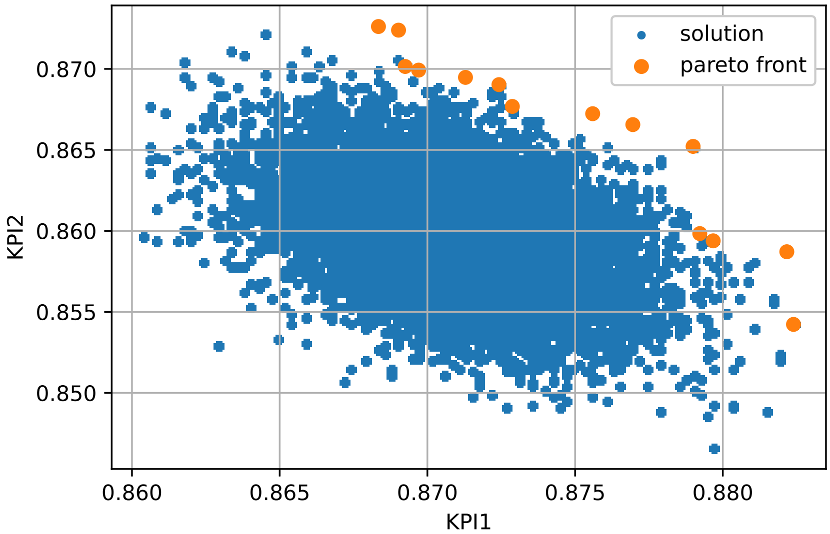

Figure 4. The distribution of the performance of the generated solutions on the first two KPIs with the selection of the Pareto front

On KPI2 a_{13} is worse than a_7 by more than the indifference threshold, however, less than the preference threshold; thus, the marginal concordance function shall be calculated as follows:

$$c_2(a_{13}, a_7) = \frac{(0.8587 - 0.8677 + 0.02)}{(0.02 - 0.005)} = \frac{0.011}{0.15} = 0.7(3) \tag{6}$$

On KPI5, a_{13} is worse than a_7 by more than the preference threshold; therefore, the marginal concordance function is equal to zero. The marginal discordance function shall be calculated in the following way.

$$d_5(a_{13}, a_7) = \frac{0.6273 - 0.6222 - 0.005}{0.02 - 0.005} = \frac{1}{150} = 0.00(6) \tag{7}$$

Finally, one can calculate the comprehensive concordance index as

$$C(a_{13}, a_7) = \frac{(1 \times 5 + 0.7(3) \times 5 + 1 \times 3 + 1 \times 2 + 0 \times 2 + 1 \times 3 + 1 \times 2 + 1 \times 1)}{(5 + 5 + 3 + 2 + 2 + 3 + 2 + 1)} \approx 0.855 \tag{8}$$

After including the marginal discordance function, one can obtain the credibility of an outranking relation for that pair of alternatives.

$$\sigma(a_{13}, a_7) = 0.855\,(1 - 0.00(6)) = 0.8493 \tag{9}$$

After applying this procedure to each ordered pair of alternatives, a matrix that contained the credibilities of an outranking relation was created. Then, within the NFS procedure, the final score can be calculated individually for each alternative. The obtained scores are presented in Table 4. Alternative a_9

attained the highest score, thus it was recommended as the best schedule generated with the genetic approach. Two main factors have decided to recommend the solution a_9. First, it is placed in the middle of the Pareto front with respect to the two most important criteria, and hence, when compared with other alternatives in most comparisons, it is not worse by more than the indifference threshold. It results in a high number of outranked alternatives which causes a relatively high value of a positive flow. Secondly, the alternative has an outstanding performance on criterion g_4. The difference in evaluations on this criterion between a_9 and other alternatives is nearly always higher than the preference threshold and sometimes even above the veto threshold. This fact impacts the value of the marginal discordance function which later invalidates the outranking relation over a_9, thus the negative flow of this alternative is the lowest. Relatively high positive flow with the lowest negative flow results in the highest overall score.

Table 4. Final scores for Pareto front

Name	φ_i^+	φ_i^-	s_i
a_1	8.23	9.57	–1.35
a_2	8.28	9.55	–1.27
a_3	2.73	11.92	–9.2
a_4	4.78	10.8	–6.02
a_5	10.78	7.75	3.03
a_6	7.832	8.52	–0.69
a_7	11.99	9.01	2.98
a_8	3.97	12.95	–8.98
a_9	12.73	5.0	7.73
a_{10}	13.33	6.38	6.95
a_{11}	12.36	7.83	4.52
a_{12}	12.34	7.65	4.69
a_{13}	11.43	6.71	4.72
a_{14}	3.89	11.02	–7.13

6. Conclusions

The main aim of this publication was to provide an example of the implementation of an IT system for human work planning using advanced mathematical algorithms. The business case is based on data collected from different sources and levels of detail, which are used together to create work plans. The introduction of a mathematical optimisation tool has helped to improve the quality of job scheduling.

Firstly, by implementing sophisticated mathematical algorithms, it was possible to expand the list of criteria and constraints that are taken into account during planning. Until now, due to the mathematical complexity of the problem, this was not always possible. In addition, the introduction of KPIs made it possible to adapt planning criteria to individual needs – thanks to the preferences of a DM, it is now possible to plan based on the prioritisation of selected goal functions.

The result of the optimisation mechanisms is the extracted Pareto front. In the course of genetic optimisation, the Pareto front is constantly improved, but at some point, the algorithm finishes due to the fulfilment of certain conditions. The Pareto front can be expressed as a table with the non-dominated alternatives. Each of the alternatives is expressed as a vector of KPIs which reflect the business value. Thus, a quite complex solution to the task assignment problem is expressed here in a very elegant and concise way. The proper definition of the KPI space allows the extraction of the essential information, which forms the basis for the subsequent application of the MCDA method. On one hand, we cope with the multi-criteria optimisation that the solution is a set of non-dominated alternatives. The NSGAII method takes care of the quality of the Pareto front, especially in the context of the uniform distribution of the solutions along the KPIs directions. On the other hand, the carefully chosen MCDA method is applied to the Pareto front to select a single solution, because, in the end, this is relevant from the practical perspective.

The article explains the basic principles of the planning process, the selected mathematical methods and tools, and the reasons for their choice. The proposed here workflow is capable of efficient treatment of the incoming planning data, turning them into suitable forms for further processing and ultimately applying the proposed here methods. The end-user can introduce the preferences in a very straightforward way and obtains a single solution that can be the subject of manual correction, or can be directly launched into the production environment. The appropriate definition of the KPIs opens the possibility of the business-oriented interpretation of the results, and thus builds trust and confidence. The presented approach provides the necessary in business applications consistency and efficiency. It combines the well-established and commonly accepted multi-objective genetic approach with the application of the MCDA method for the extraction of the final solution.

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